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ESTIMATION OF PARAMETERS OF FEED-BACK PULSE COUPLED NEURAL NETWORKS (FBPCNN) FOR PURPOSES OF MICROSTRUCTURE IMAGES SEGMENTATION

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Abstract

Although the Pulse Coupled Neural Network (PCNN) as well as FBPCNN (with feed-back) have been, since 1990, well known image analysis methods, they are still developed to solve the problems related to estimation of initial network parameters. Most of such parameters vary dependently on the character of input images (e.g. range of colors, noise strength, shapes diversity) to offer the best results. This work aims to establish parameters of the network based on FBPCNN architecture, applied in processing of images of metals' microstructures. The paper contains detailed description of implemented neural network followed by sensitivity analysis of the network on parameters' change. On the basis of the performed analysis, the parameters with major influence on the final results were determined and investigated in details. The results obtained in the process of image analysis by using proposed FBPCNN were passed as input data initiating Watershed algorithm for the purposes of segmentation. Results of segmentation are presented in the paper as well.

Key words: pulse coupled neural network, image segmentation, microstructure analysis

1. INTRODUCTION

The main motivation of the following work is foundation of Digital Material Representation (DMR) idea. The concept of DMR was recently proposed and is dynamically evolving (Bernacki et al., 2007; Dawson & Miller, 2007; Madej et al., 2007; Melchior & Delannay, 2006; Rauch & Madej, 2008; Rauch et al., 2009). Its main objective is creation of the microstructure representation with all important features represented explicitly e.g. grains, grain orientations, inclusions, cracks, different phases. This approach allows for attachment of external numerical modules, which are able to simulate various microstructural phenomena e.g. dynamic recrystallization, phase transformation, fracture and its interactions at the micro scale level.

Many various methods, dedicated to creation of virtual representation of material microstructures, were recently proposed. The most popular and widely applied groups of such methods are (Cybułka et al., 2007): Voronoi Tessellation, Cellular Automata, Sphere Growth or Image Processing (especially Image Segmentation). The latter method offers the higher reliability by returning the representation identical with real microscopic photographs of microstructure (Rauch & Madej, 2009). However, it is also the most difficult technique, because of strong variety of objects presented in images, including their shapes, colors, noise, size, non-uniform illumination, etc. Thus, application of one segmentation method for images of different materials is very difficult. Currently developed image segmentation methods in this area are designed in two different

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ways. The first direction is focused on generalization of methods to as much universal as possible. The techniques implemented in that way are characterized by independence of input data, but average quality of returned results. On the other hand, the methods dedicated for specific types of images are much more efficient and reliable, but their applicability is always limited. Thus, the main topic of the research aims to propose the image segmentation method, which represents the group of general approaches with functionality covering specific group of pictures e.g. microscopic pictures of materials, but wide enough to process diversified images. For purposes of this work Authors decided to use approach based on FBPCNN, which, similarly to many methods based on neural networks, is characterized by ability to generalize various input data. Nevertheless, the main drawback of this method is necessity of parameters' adjustment according to character of input image.

The main objective of this work is to establish the most optimal parameters of FBPCNN-based approach for initial segmentation of microstructure images. For the realization purposes the sensitivity of implemented method was analyzed and on the basis of the obtained results the best solution was determined. The selected approach is presented in details in the following section. The results obtained from image processing by using FBPCNN were passed to Watershed algorithm responsible for segmentation. Original, processed and segmented images are presented in the paper as well.

2. FEED-BACK PULSE COUPLED NEURAL NETWORK

2.1. FBPCNN concept

In early 90' Eckhorn observed oscillatory activities which were stimulated by external stimulus in cat's primary visual cortex (Eckhorn, 1994). Some of those signals caused synchronous oscillations in distant regions of the cortex, characterized by local similarities. The main result of this research was creation of neural model able to simulate mechanism of visual cortex. Proposed model was recognized as having significant application potential in image processing area and was finally adapted for the purposes of sophisticated approaches based on neural networks architecture. Each neuron, being the basic element of such network, is made of three fundamental elements i.e. Linking Field, Feeding Field (Stimulus) and Pulse Generator (figure 1).

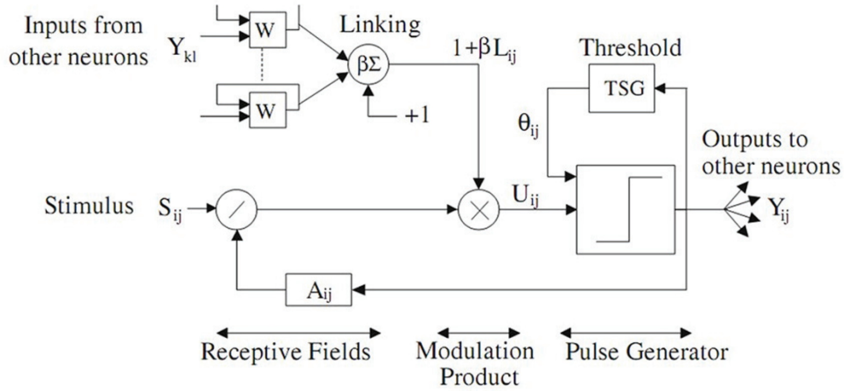

Fig. 1. *Model of neuron applied in FBPCNN architecture.*

The Linking and Feeding Fields are responsible for gathering signals generated by adjacent neurons. Each of the connections between neighboring neurons is parameterized by weights describing its relevance. In case of images, these weights can be related to distances between pixels or difference between their colors. The role of Pulse Generator is similar to typical activation functionality. It is responsible for generation of Heaviside signal, where '1' means neuron being activated, otherwise '0' is returned.

The calculations of these values are performed on the basis of summation of results obtained from Linking Field and Stimulus. Values of Linking Field (L_{ij}) for each neuron are calculated as follows:

$$L_{ij}[n] = e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} W_{ijkl} Y_{kl}[n-1] \tag{1}$$

where α_L is delay coefficient, i, j are indexes of neuron inside a network, W_{ijkl} are weights defined for connections between neuron ij and its neighbors kl, Y_{kl} represents input obtained from adjacent neuron and V_L is the global constant which is used to scale dependence between adjacent neurons. Calculated linking values are crossed with external stimulus and passed as input neuron activity to Pulse Generator in form of U_{ij} value calculated in eq. 2.

$$U_{ij}[n] = S_{ij}[n]\left(1+\beta L_{ij}[n]\right) \tag{2}$$

where S_{ij} is a value of Feeding Field and β describes strength of linking. Final neuron activity is calculated by using the following unit step function:

$$Y_{ij}[n] = \begin{cases} 1, & U_{ij}[n] > \theta_{ij}[n]; \\ 0, & otherwise. \end{cases} \tag{3}$$

where θ_{ij} is threshold value in Pulse Generator. After neuron's activation the value of θ_{ij} is set higher than its global average and modified according to eq. 4. This allows to avoid constant activation or deactivation of the neuron.

$$\theta_{ij}[n] = e^{-\alpha_\theta}\theta_{ij}[n-1] + V_\theta Y_{ij}[n-1] \qquad (4)$$

where α_θ is a delay coefficient, V_θ is a feed-back parameter of influence of output value on θ_{ij}. The feed-back is obtained also by influence of additional A_{ij} values, which is calculated on the basis of output, α_A and V_A values according to eq. 5. The result of this calculations has impact on Feeding Field and modifies the signal flowing to Pulse Generator (eq. 6).

$$A_{ij}[n] = e^{-\alpha_A} A_{ij}[n-1] + V_A Y_{ij}[n-1] \qquad (5)$$

$$S_{ij}[n] = S_{ij}[n-1] / A_{ij}[n-1] \qquad (6)$$

The combination of equations 1-6 offers interesting pulsing behavior of the neurons, however the values of mentioned above parameters are strongly related to input data and assumed architecture of the network.

2.2. Network architecture

FBPCNN networks are characterized by unique architecture, where neurons are organized in a cellular way as 2D matrix (figure 2). Each neuron is connected with set of other neighboring neurons, which can be easily mapped on the structure of images containing neighboring pixels. In that case, amount of neurons reflects the amount of pixels inside input image.

According to such architecture different neighborhood types can be defined, which is similar to concept of the neighborhood in Cellular Automata. However, the neighborhoods in FBPCNN are dependent on assumed radius. The most popular approaches are presented in figure 3.

The average greyscale value of the pixel and all adjacent pixels are usually passed on input of Feeding Field, which is modified in the following iterations by feed-back parameter. Thus, properly configured network is characterized by pulsing periods, where one period is described as a distance between two global maximums in network activity graph. The graph presents amount of lightened pixels in each iteration. It was empirically found that second maximum in such graph determines the iteration, which offers the best starting points for segmentation algorithms e.g. markers for the watershed algorithm. However, this is based on subjective human assessment and it has been not proved yet as well as the results obtained after segmentation have not been evaluated. This area of research is still under discussion.

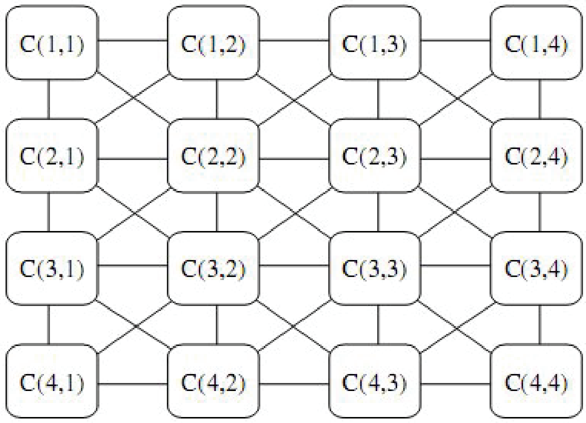

Fig. 2. *Architecture of FBPCNN. C(x,y) means the neuron in x^{th} row and y^{th} column.*

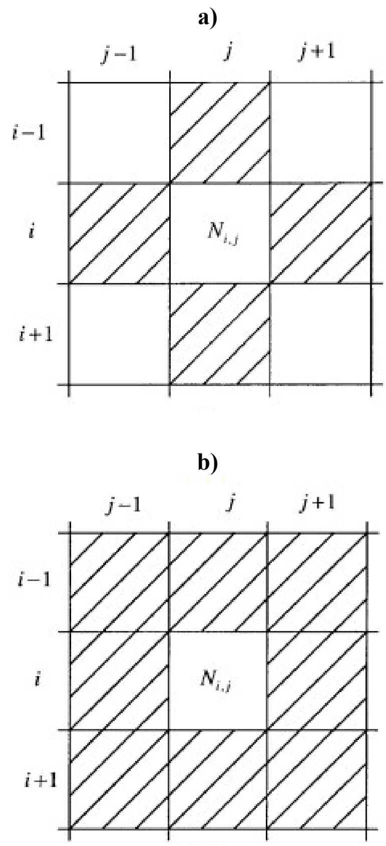

Fig. 3. *Neighboring neurons in case of radius r=1.0 (a) and radius r=1.5 (b).*

3. ALTERNATIVE IMAGE SEGMENTATION METHODS

The image segmentation algorithms are one of the most explored methods in the literature. For at least two decades hundreds of papers have been published in this research area. Existing approaches can be divided into several subgroups depending on the type of the algorithms e.g. template matching, edge detection, tracing as well as depending on the type of implemented numerical techniques e.g. matrices convolution, artificial intelligence or nature inspired (neural networks, content-based analysis, cognitive recognition), clustering, statistical approaches, nonlinear diffusion analysis. Such algorithms play very important role not only in analysis of the 2D pictures, but also in the 1D signals and 3D images processing, and multidimensional calculations. However their complexity increases respectively to increase in data dimensionality. In the case of microstructure photographs analysis all of the mentioned methods can be more or less successfully applied. Thus, the review of the most recent papers regarding this field of research can be enumerated as follows:

– Convolution – in practice, well-known and widely applied methods based on derivative operators. Such methods are very flexible and simple in implementation by using special kernel matrices e.g. Prewitt or Sobel to obtain effect of edge detection (Nixon & Aguado, 2002).
– Nature inspired – one of the most popular methods is Watershed algorithm, which originates from natural solution of landscape and watersheds (Bleau & Leon, 2000; Zhao & Zhuang, 2005). The idea of this method is based on the initial segmentation of data into disjoint areas, which in the next steps are filled successively with water puddles until two of them meet. The Authors proposed also the application of special type of Watershed method implemented by using CA (Rauch & Straus, 2009), which offers high flexibility in case of various images, their shapes, colours, etc.
– Nonlinear diffusion – technique of image processing based on nonlinear diffusion and popularized by Perona and Malik (1990). This method was further modified and improved for applications in the area of texture-based segmentation. The example of such approach is presented by Zhang (2008), where author proposes to measure the scale of texture by using nonlinear diffusion followed by the multi-channel statistical region active contour adaptation. The method can be seen as a kind of unsupervised segmentation, because parameters are not sensitive to different texture images.
– Clustering-based – these approaches are sufficient mainly for images without additional distortions, however their efficiency in case of even slightly noised data is very poor (Liew et al., 2005). Thus, the modifications of such methods with other computational techniques like optimization procedures are often proposed (Zhou et al., 2008). The main advantage of this solution is higher insensibility for distortions, which offers much more reliable results.

The process of segmentation is very sophisticated and obtained results can be highly diversified even for the same input data and algorithm. This phenomenon depends mainly on the parameters established for the selected algorithm. Moreover, the automated assessment of the results is very difficult, thus it is hard to design the universal segmentation method able to work on various types of images. The proposition of a method dedicated to assess segmentation results is presented by Shah (2008). This approach consists of the framework based on Bayesian network, which determines optimal segmentation algorithm through a specific learning process. Another assessment methods was proposed by Authors in (Rauch & Straus, 2009), which is based on the calculation of fractal dimension offering higher efficiency and slightly different quality measure of the results. Wider review of unsupervised evaluation techniques, which offers objective comparison of different segmentation methods, is presented by Zhang et al. (2008).

4. SENSITIVITY ANALYSIS

The analysis of sensitivity of proposed FBPCNN network was performed for all neuron parameters used to calculate pulsing values. The influence of parameters on final results were analyzed within the following ranges: α_θ [-1.0, 1.0], V_θ [-50.0, 200.0], α_L [-1.0, 1.0], V_L [0.0, 10.0], α_A [-0.15, 1.0], V_A [0.0, 1.0] and β [0.0, 1.0]. The comparison of results obtained for different values of parameters allowed to separate the parameters with minor influence on final result and to determine the most important coefficient, which is β. Therefore, the detailed analysis was performed for β and divided into two directions: value of the parameter were varying in the range of [0.0, 1.0] or it was established dynamically by application of the following equations:

$$\beta_{ij} = \sqrt{\frac{V_{ij}}{M_{ij}}} \tag{7}$$

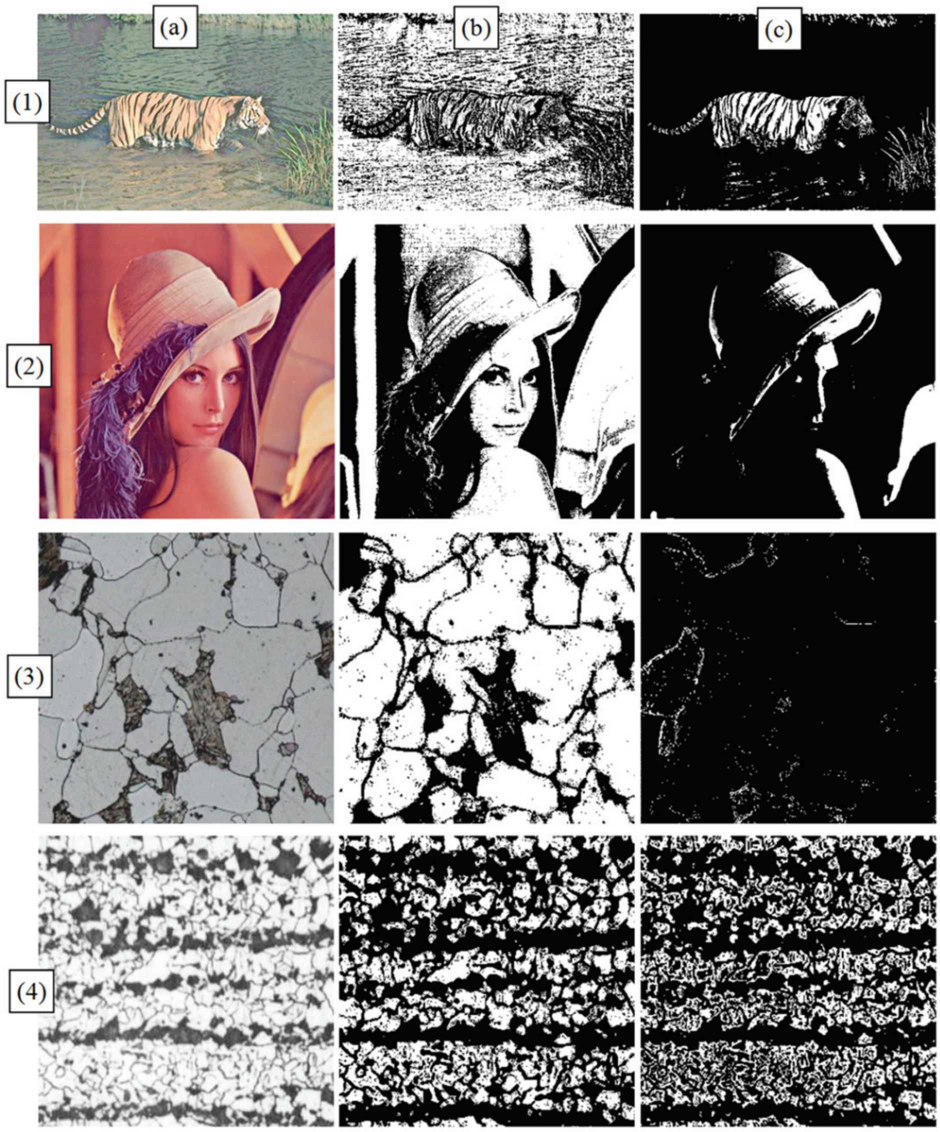

Fig. 4. Rows: (1) Tiger image[1]*, (2) Lena Image, (3) DP microstructure (large grain size), (4) DP microstructure (small grain size). Columns: Original input image (a), result obtained with β calculated per pixel (b), result obtained with constant β=0.2 for all pixels (c).*

where i, j corresponds to coordinates of pixels, M is mean and V is variation. M is calculated using values of colors (S_{ij}) of neighboring N pixels:

$$M_{ij} = \frac{1}{N}\sum_{kl} S_{ij} \tag{8}$$

On the basis of mean value and colors values the variation is calculated:

$$V_{ij} = \left(S_{ij} - M_{ij}\right)^2 \tag{9}$$

The estimation of β parameters using equations 7-9 was proposed by Johnson (1993) and modified later by Yingwey et al. (2004). In most cases it was used in this form for greyscale images. In this work it was applied for greyscale as well as colored images. The results obtained for constant and dynamically calculated β are presented in figure 4.

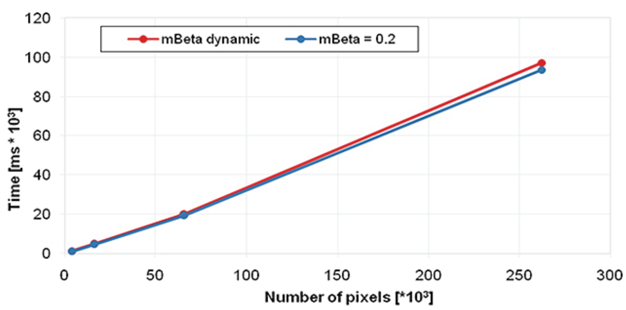

Fig. 5. Comparison of network performance for constant and dynamic β parameter.

[1]http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds / - Berkeley Segmentation Dataset

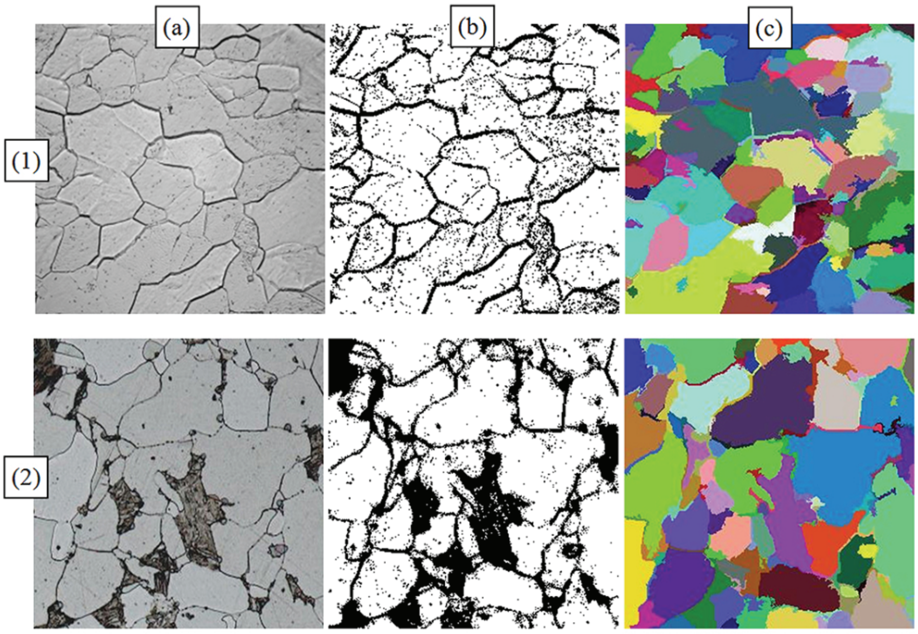

Fig. 6. *Rows: (1) One phase material, (2) DP microstructure. Columns: Original input image (a), result obtained with β calculated per pixel (b), results of Watershed segmentation (c).*

Performed tests shows that in most cases network is more active when β is dependent on input image and is dynamically calculated on the basis of equation 7-9. This approach allows to diversify this parameter for each pixel instead of using constant value, what highly influences quality of obtained results e.g. figure 4, image 3. On the other hand, the approach can easily cause undesirable effect of oversegmentation (figure 4, image 1b), leading to large set of small size segments. Therefore, the final value of β should be estimated according to equations, which consider number of segments and a feedback information about a quality of segmentation. Such approach will allow to apply advanced optimization methods able to determine the parameters for input image offering the best segmentation effect. This issue will be the main direction of future research focused on development of the proposed method.

Dynamic calculations of β parameter has minor influence on computational complexity and time required for network performance (figure 5).

5. SEGMENTATION RESULTS

The results obtained from proposed FBPCNN were passed to Watershed algorithms as starting points for flooding procedure. The algorithm of Watershed realized on the basis of cellular automata was applied (Rauch & Straus, 2009). The connection of these two methods allowed to perform segmentation process of microscopic pictures of different types of materials. The results are presented in figure 6.

6. IMPLEMENTATION DETAILS

The computer program, used for analysis of FBPCNN network, was implemented in C++ based on object-oriented design (the source codes are available at http://www.cmms.agh.edu.pl/public_repo/fbpcnn.rar). Basically, it consists of two classes i.e. *CNetwork* and *CNeuron*. Performance of the program is started by internal *run* method of *CNetwork* class, which setup all startup parameters of the network and calls iteratively the calculations of the neurons' weights by using *calculateValues* function from *CNeuron* class (table 1).

The function determines a neighborhood of the neuron by running *getAdjacentNeurons(r)* procedure, which creates list of adjacent neurons in radius r. Then, if β parameter is not constant, the dependencies between neighboring neurons are calculated influencing values of mean (M), variance (V) and parameter β (*mBeta*). Finally, all neuron parameters described in section 2.1 are calculated on the basis of startup or previous iteration values. The mentioned parameters are marked as follows: sum of values of adjacent neurons (mSum), $L_{ij}[n]$ (mL_ij[n]), $S_{ij}[n]$ (mS_ij[n]), $U_{ij}[n]$ (mU_ij[n]), $\theta_{ij}[n]$ (mTreshold[n]), $A_{ij}[n]$ (mA_ij[n]), $Y_{ij}[n]$ (mY_ij[n]).

Implementation of basic image processing methods was based on AForge.NET numerical library (http://code.google.com/p/aforge/).

Table 1. Implementation of the main method dedicated to calculation of neurons values in each iteration.

```
void CNeuron::calculateValues(int n) // n - current iteration number
{
   getAdjacentNeurons(1.0f);
   if (!mBetaConst)
   {
       float M = 0.0f, V = 0.0f;
       for (int i = 0; i < mAdjacentNeurons->Count; i++)
          M += dynamic_cast<CNeuron^>(mAdjacentNeurons[i])->getValue();
       M /= mAdjacentNeurons->Count;
       V = (getValue() - M) * (getValue() - M);
       if (M == 0)
          mBeta = 0.0f;
       else
          mBeta = float(Math::Sqrt(V) / M);
   }
   mSum = 0.0f;
   for (int i = 0; i < mAdjacentNeurons->Count; i++)
      mSum += (float)(mW_ij[i]) * dynamic_cast<CNeuron^>(mAdjacentNeurons[i])->getValue(n-1);
   mL_ij[n] = float(Math::Pow(float(Math::E),-mAlfa_L)) * mL_ij[n-1] + mV_L * mSum;
   mS_ij[n] = mS_ij[n-1] / mA_ij[n-1];
   mU_ij[n] = mS_ij[n] * (1+mBeta*mL_ij[n]);
   mTreshold[n] = float(Math::E^-(mAlfa_Treshold))*mTreshold[n-1] + mV_Treshold * mY_ij[n-1];
   mA_ij[n] = float(Math::E^(-mAlfa_A)) * mA_ij[n-1] + mV_A * mY_ij[n-1];
   mY_ij[n] = (mU_ij[n] > mTreshold[n]) ? 1.0f : 0.0f;
}
```

7. CONCLUSIONS

The estimation of parameters of FBPCNN in the process of image segmentation was presented in the paper. On the basis of sensitivity analysis of the network, the β parameter, which has major influence on final results, was selected. The analysis of this parameter was performed using two approaches to verify if its dynamic estimation for each neuron will improve the quality of further segmentation process. To realize this objective the proposed FBPCNN was connected with watershed algorithm implemented using cellular automata technique. Due to such connection the results of the network could be easily passed to the segmentation method as starting points of iterative flooding. The results obtained for typical testing images as well as pictures of material microstructures gathered from optical microscope showed that in most cases β calculated dynamically will offer better segmentation results than its constant value. However, the quality of results can be still improved by considering final number of segments to avoid effect of oversegmentation. Thus, the next step of the research will be focused on application of an evaluation method of segmentation results. Such algorithm will allow to apply optimization methods to determine the parameters to obtain the highest quality of results.

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ANALIZA WRAŻLIWOŚĆ SIECI FBPCNN W PROCESIE PRZETWARZANIA ZDJĘĆ MIKROSTRUKTUR MATERIAŁOWYCH

Streszczenie

Sieci Pulse Coupled Neural Network (PCNN) jak i również FBPCNN (ze sprzężeniem zwrotnym) zostały po raz pierwszy zaproponowane już z początkiem lat 90' i od tego czasu są bardzo dobrze znanym narzędziem wykorzystywanym m.in. do przetwarzania obrazów. Pomimo tak długiego czasu, metody oparte o FBPCNN są nadal rozwijane, a największym wyzwaniem jest wciąż dobór najlepszych parametrów wagowych sieci dla obrazu wejściowego. Celem niniejszej pracy jest zbadanie możliwości zastosowania pulsujących sieci neuronowych do przetwarzania zdjęć mikrostruktur materiałowych oraz wyznaczenie jej optymalnych parametrów dla tego przeznaczenia. Artykuł zawiera szczegółowy opis zaimplementowanej sieci neuronowej oraz wykonanej analizy wrażliwości FBPCNN na zmianę jej parametrów wagowych. Na bazie wykonanej analizy wyznaczone zostały parametry charakteryzujące się znaczącym wpływem na otrzymywane wyniki. Dla wybranego parametru (beta) zaproponowano jego modyfikację tak, aby parametr dobierany był w sposób automatyczny w zależności od obrazu wejściowego. Otrzymane wyniki posłużyły jako dane wejściowe od algorytmu Watershed, za pomocą którego wykonano finalną segmentację obrazów mikrostruktur. Rezultaty procesu segmentacji wraz z dyskusją zostały również przedstawione w niniejszej pracy.

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